

Bayesian Anomaly Detection for Ia supernovae using JAX-bandflux

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Outline

JAX and JAX-bandflux

Bayesian anomaly detection

Apply on Ia supernovae

JAX and JAX-bandflux

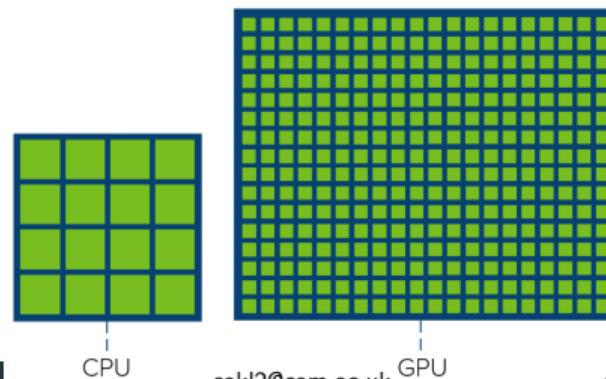
What is JAX

- JAX is a high-performance numerical computing library
- Combines NumPy-like functionality with:
 - Automatic differentiation (like TensorFlow/PyTorch)
 - Just-in-time (JIT) compilation
 - GPU/TPU acceleration
- Fundamentally, allows us to run highly parallelized operations on powerful GPUs



Why do we care about doing things on GPUs

- Massive parallelization capabilities
 - CPUs: Few cores (4-64), high clock speeds
 - GPUs: Thousands of cores, designed for parallel tasks
 - Significant performance improvements for numerical computations
- Useful for astronomical applications
 - Processing large datasets (e.g., supernova surveys)
 - Running complex simulations (e.g., SBI)
 - Performing parameter inference with many samples



Limitations in JAX

- Vectors length must be defined at compilation

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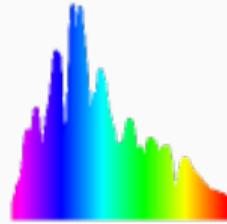
- Vectors length must be defined at compilation
- Limited control flow (no while loops, etc)
- Debugging and optimising is hard

JAX numpy vs numpy

```
import numpy as np
x = np.arange(10)
y = np.zeros_like(x)
for i in range(len(x)):
    y[i] = x[i] * 2
```

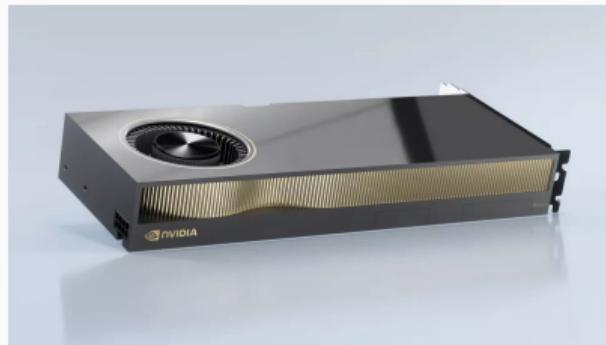
```
import jax.numpy as jnp
from jax import vmap
x = jnp.arange(10)
def double(v):
    return v * 2
y = vmap(double)(x)
```

What is JAX bandflux?



sn cosmo

A Python Library for Supernova Cosmology



What does JAX-bandflux do?

$$F(p, \lambda) = x_0 [M_0(p, \lambda) + x_1 M_1(p, \lambda) + \dots] \times \exp[c CL(\lambda)] \quad (1)$$

IN:

- x_0, x_1, t_0, c
- $M_0(p, \lambda), M_1(p, \lambda)$
- p (phase/redshift)
- $CL(\lambda)$

OUT:

- Flux: $F(p, \lambda)$

Bandflux Computation

- Bandflux: Integrated flux through a specific filter

$$\text{bandflux} = \int_{\lambda_{\min}}^{\lambda_{\max}} F(\lambda) \cdot T(\lambda) \cdot \frac{\lambda}{hc} d\lambda \quad (2)$$

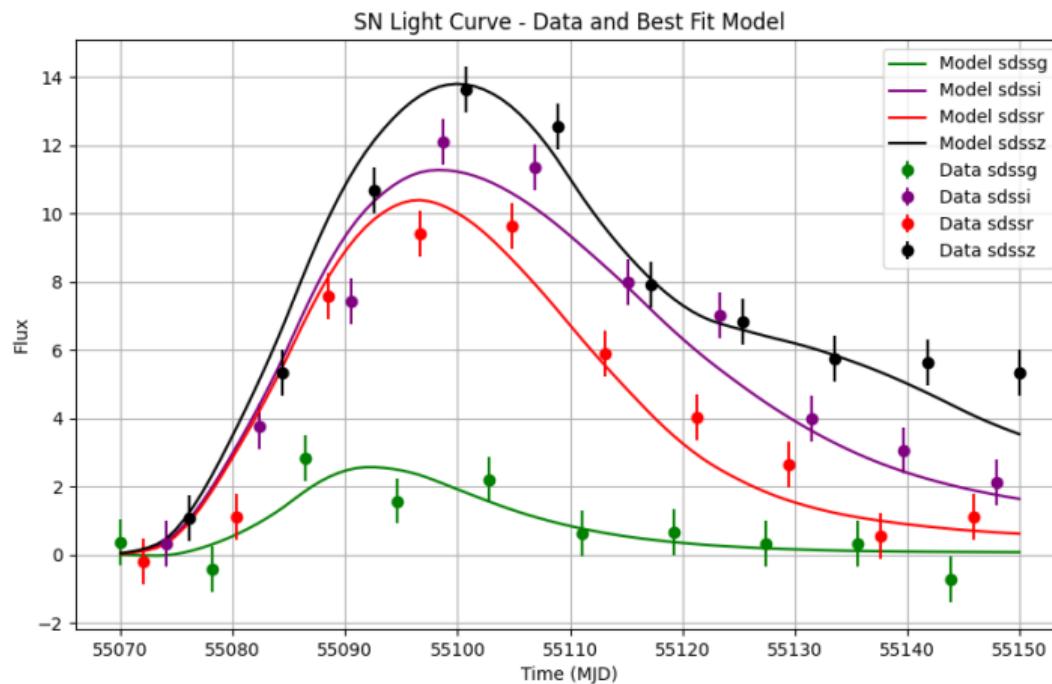
- Components:
 - $F(\lambda)$: Spectral flux density
 - $T(\lambda)$: Filter transmission function
 - $\lambda/(hc)$: Conversion from energy to photon counts
- Implementation in JAX-bandflux:
 - Vectorized array operations
 - JIT-compiled for efficiency
 - Trapezoidal integration along wavelength dimension
 - Parallelized across multiple data instances via `vmap`

Can now construct GPU compatible likelihood

$$\mathcal{L}(\mathbf{F} \mid \theta) = \prod_i \frac{1}{\sqrt{2\pi} \sigma_i} \exp \left[-\frac{(F_i - \mu_i(\theta))^2}{2 \sigma_i^2} \right]$$

- Observed fluxes F_i : measured data; model fluxes $\mu_i(\theta)$: predicted flux given parameters
- With this likelihood we can now perform parameter estimation
- Likelihood is differentiable and can be compiled as part of broader GPU workflows

Can now fit light curves on GPU

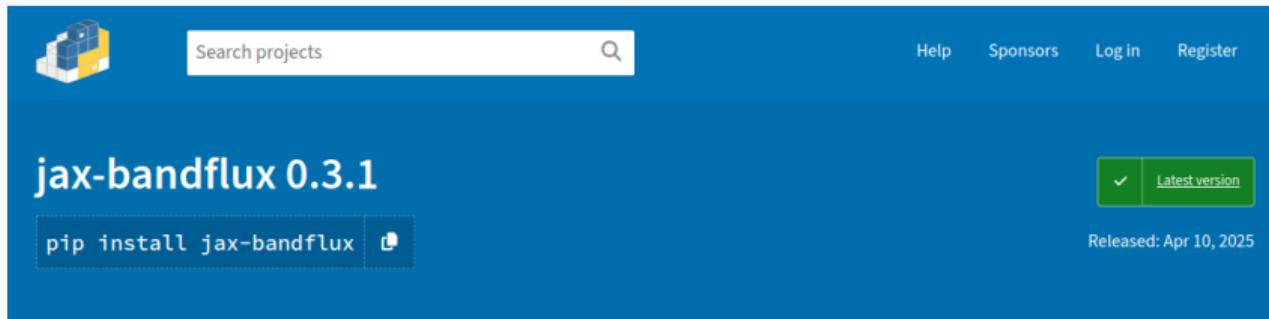


Bandflux Computation Example

- For a detailed walkthrough of bandflux computation:
 - Interactive Jupyter notebook with step-by-step implementation
 - Demonstrates JAX-bandflux API usage
 - Shows performance benefits of GPU acceleration
 - Includes visualization of results
- Access the example notebook:

Supernovae Analysis Example Notebook

PIP installable



JAX-bandflux: differentiable supernovae SALT modelling
for cosmological analysis on GPUs

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Bayesian anomaly detection

Over simplified example of anomaly detection method (thresholding)

Simple statistical approach:

- Calculate mean (μ) and standard deviation (σ) of the data
- Define threshold $T = \mu + k\sigma$ where k is a sensitivity parameter
- Flag data point x_i as anomalous if:

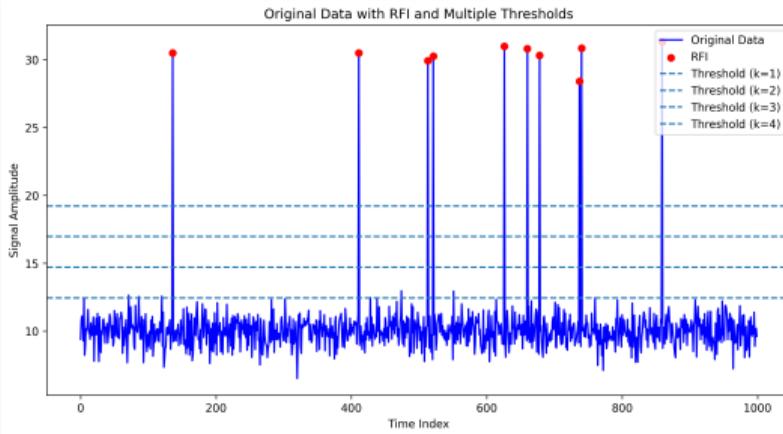
$$\text{anomaly}_i = \begin{cases} 1 & \text{if } x_i > T \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Limitations:

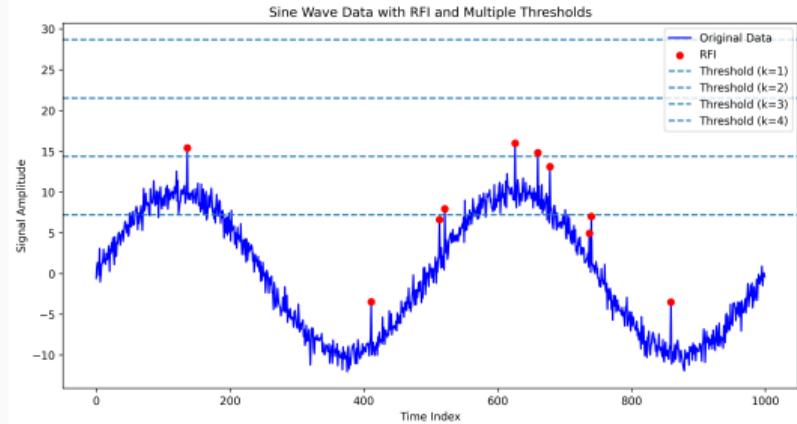
- Choice of k is arbitrary
- Assumes Gaussian statistics
- No consideration of temporal correlations
- Cannot distinguish between RFI and real signals

Thresholding results

Constant signal with RFI:



Sine wave with RFI:



Defining an anomaly sensitive likelihood

a) Generate piecewise likelihood:

$$P(\mathcal{D}_i|\theta) = \begin{cases} \mathcal{L}_i(\theta) & : \text{expected} \\ \Delta^{-1}[0 < \mathcal{D}_i < \Delta] & : \text{anomalous,} \end{cases} \quad (4)$$

b) Ascribe Bernoulli prior:

$$P(\varepsilon_i) = p^{(1-\varepsilon_i)}(1-p)^{\varepsilon_i}. \quad (5)$$

c) Marginalise over epsilon:

$$P(\mathcal{D}|\theta) = \sum_{\varepsilon \in \{0,1\}^N} P(\mathcal{D}, \varepsilon|\theta) \quad (6)$$

d) Approximate correct mask is most likely

$$P(\mathcal{D}|\theta, \varepsilon_{\max}) \gg \max_j P(\mathcal{D}|\theta, \varepsilon^{(j)}), \quad (7)$$

e) Loglikelihood:

$$\log P(\mathcal{D}|\theta) = \sum_i [\log \mathcal{L}_i + \log(1-p)] \varepsilon_i^{\max} + [\log p - \log \Delta] (1 - \varepsilon_i^{\max}) \quad (8)$$

Computing the Posterior

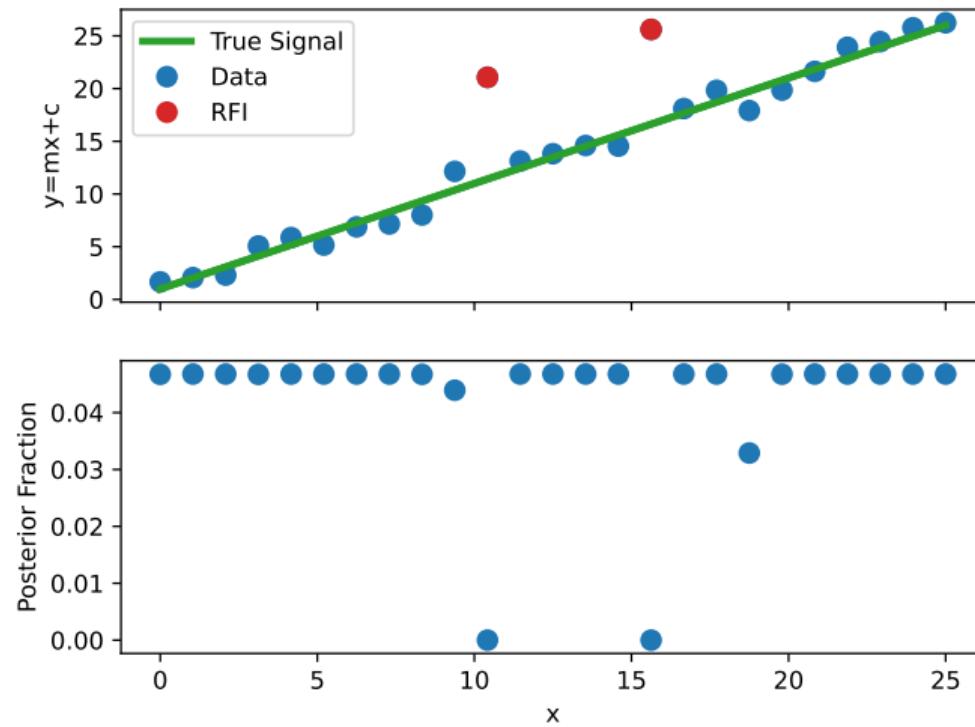
e) Loglikelihood:

$$\log P(\mathcal{D}|\theta) = \sum_i [\log \mathcal{L}_i + \log(1-p)]\varepsilon_i^{\max} + [\log p - \log \Delta](1 - \varepsilon_i^{\max}) \quad (6)$$

f) Maximise ε^{\max} by comparing the terms:

$$\log P(\mathcal{D}|\theta) = \begin{cases} \log \mathcal{L}_i + \log(1-p), & \text{if } [\log \mathcal{L}_i + \log(1-p) > \log p - \log \Delta] \\ \log p - \log \Delta, & \text{otherwise} \end{cases} \quad (7)$$

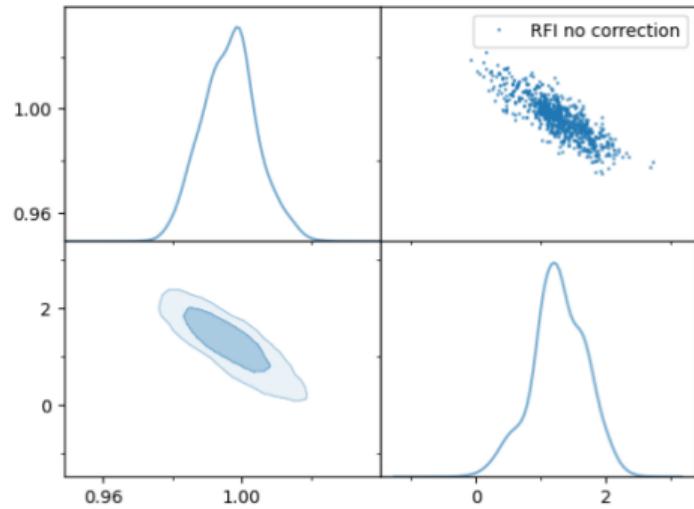
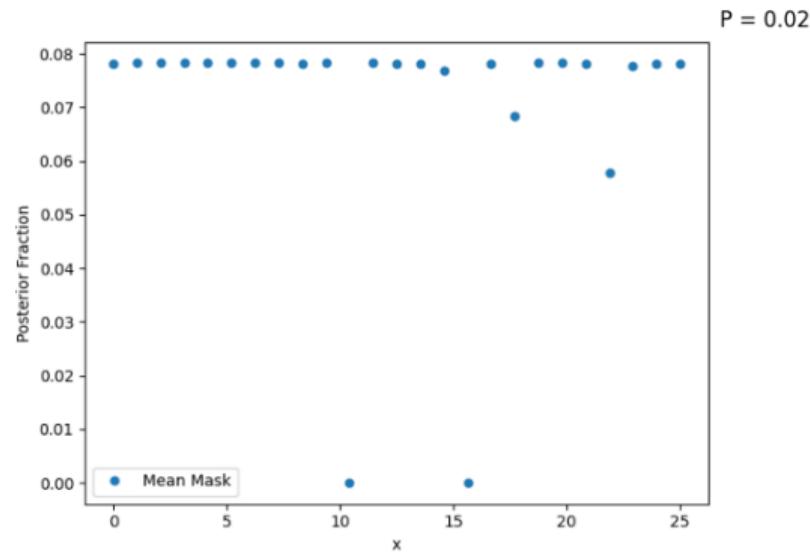
Fit on a simple toy model



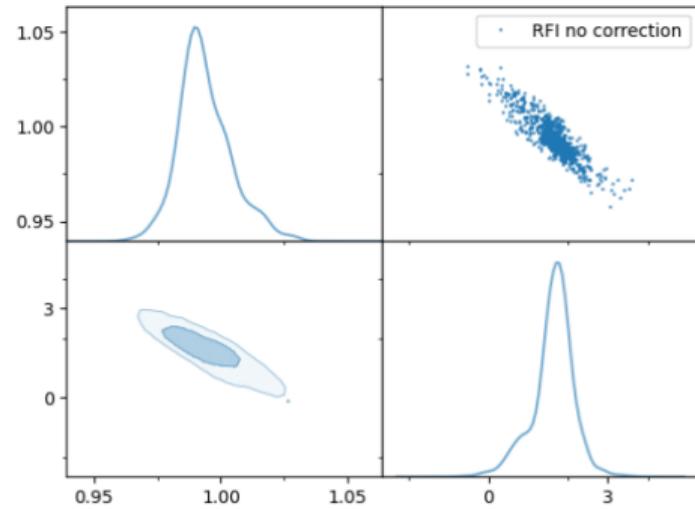
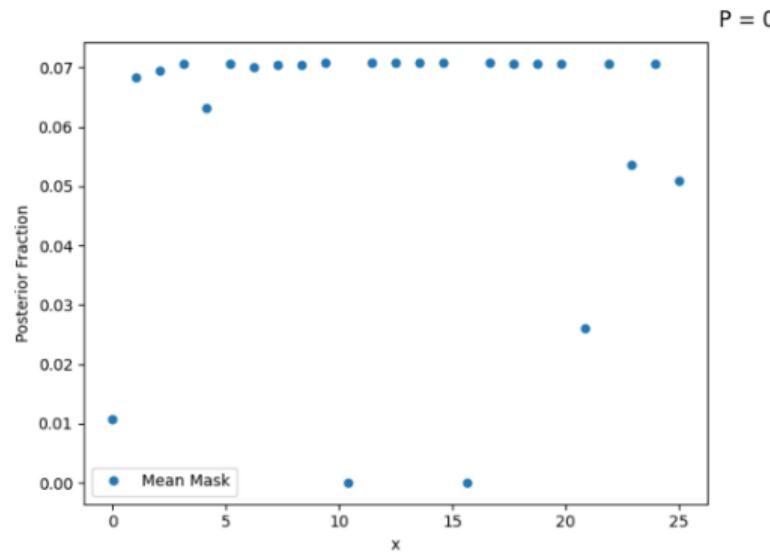
Likelihood thresholding condition p

$$\log P(\mathcal{D}|\theta) = \sum_i [\log \mathcal{L}_i + \log(1-p)]\varepsilon_i^{\max} + [\log p - \log \Delta](1 - \varepsilon_i^{\max}) \quad (9)$$

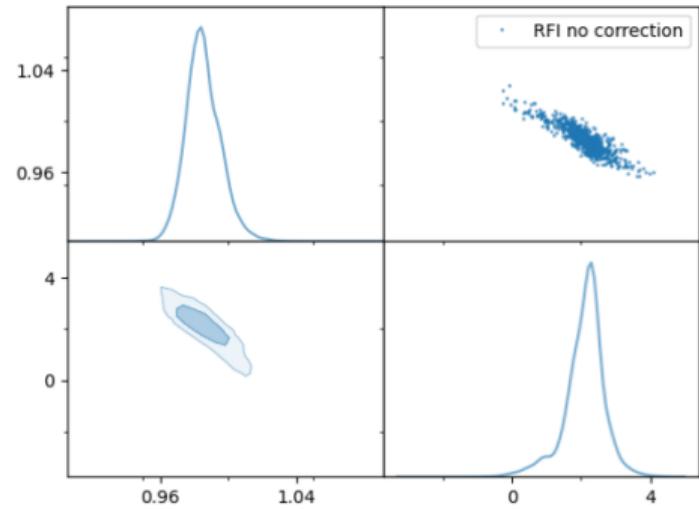
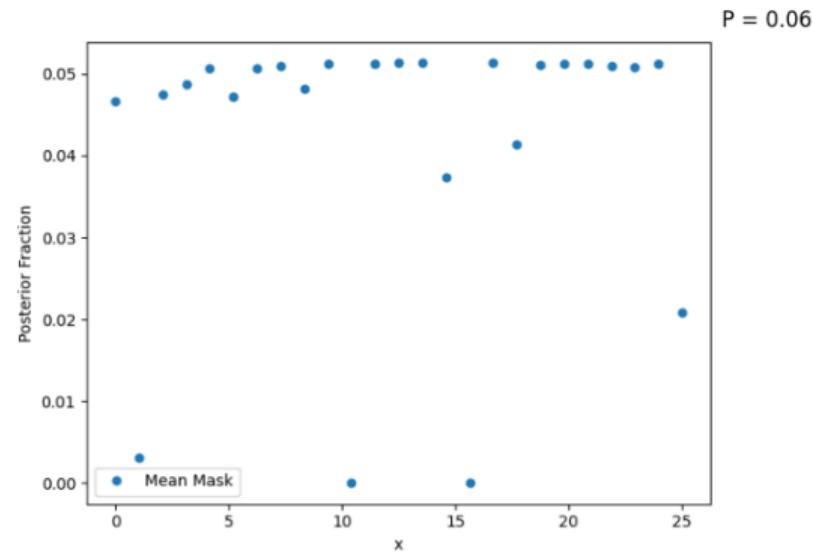
Varying p



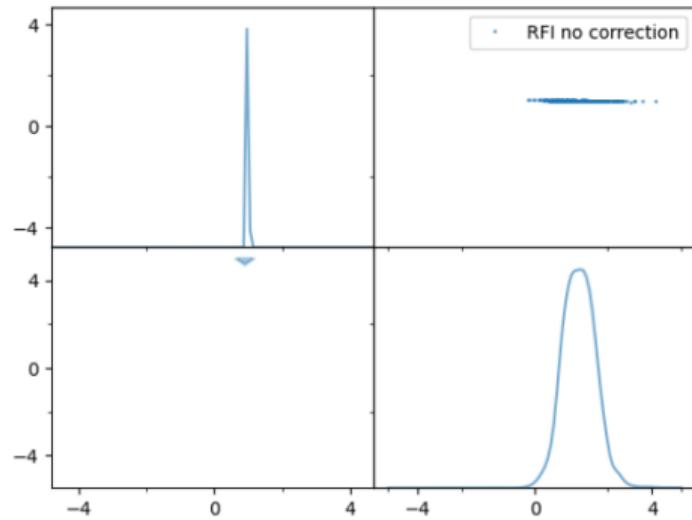
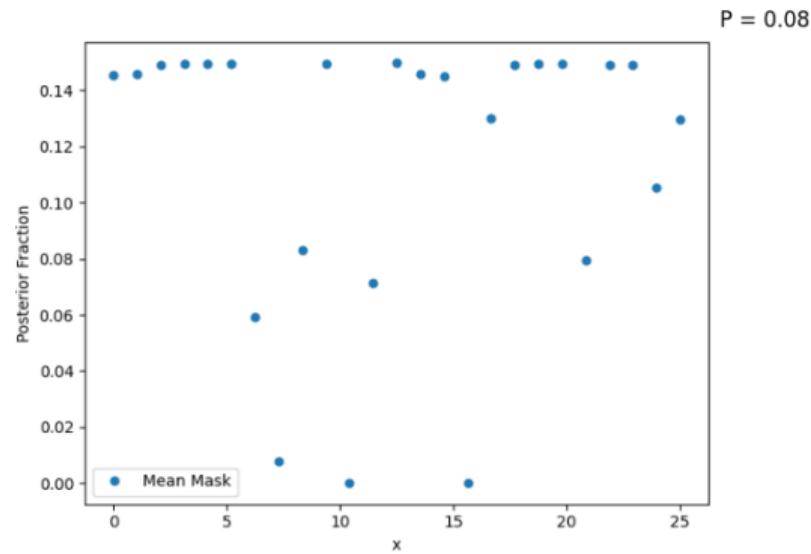
Varying p



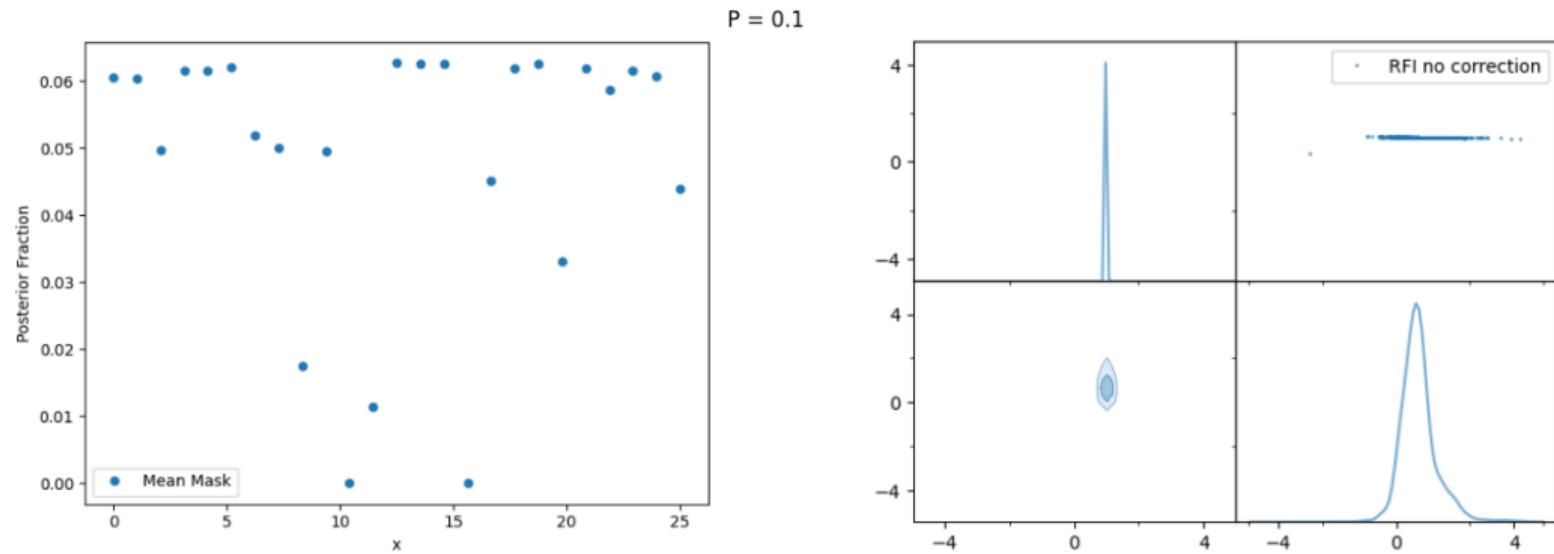
Varying p



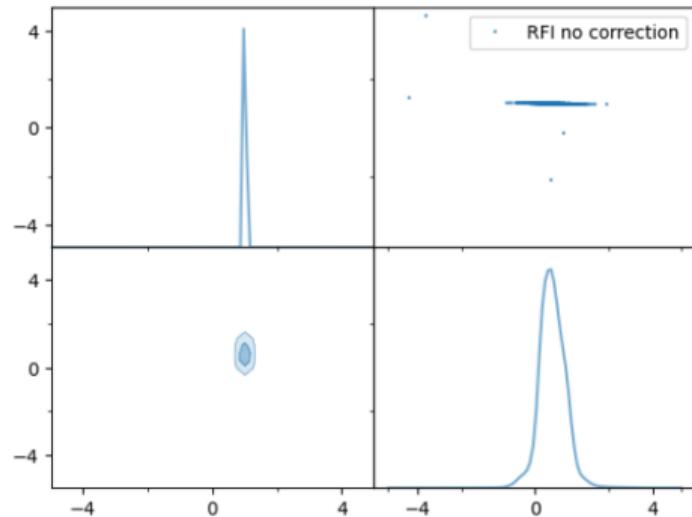
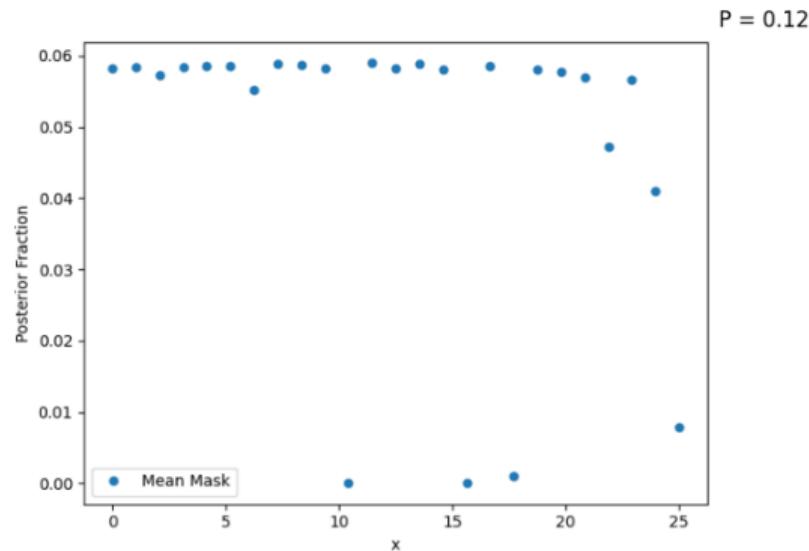
Varying p



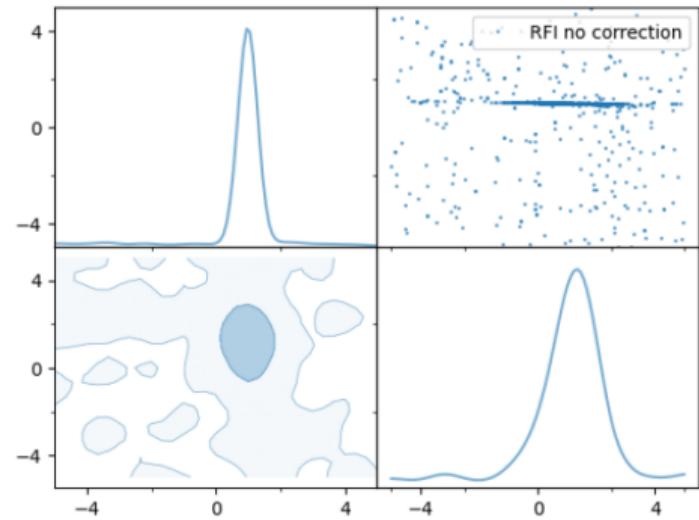
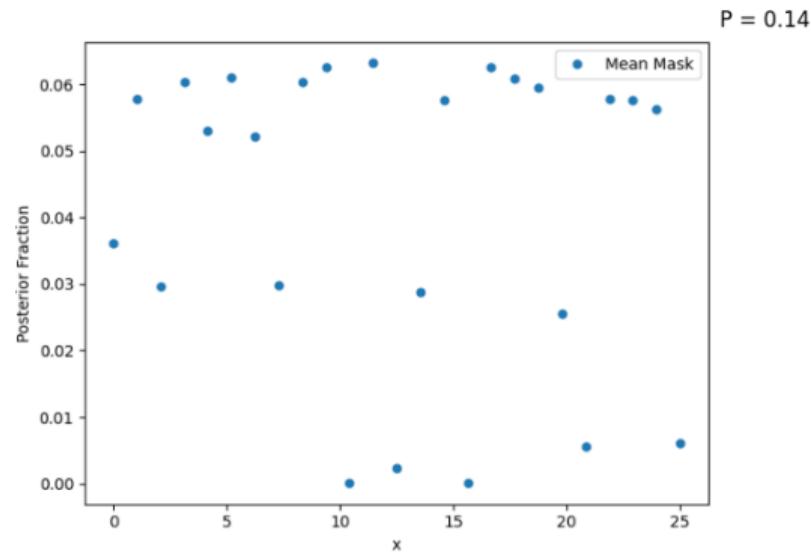
Varying p



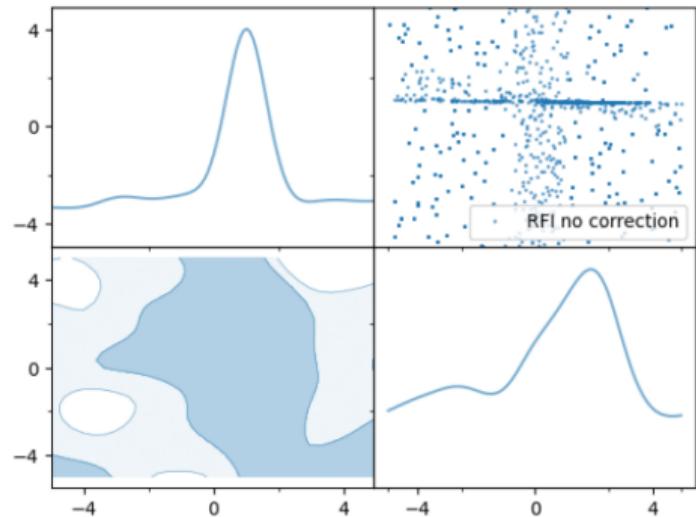
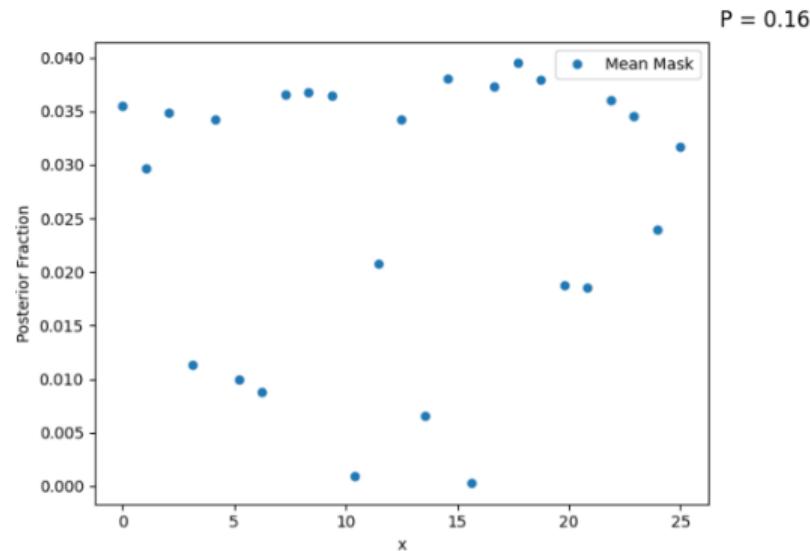
Varying p



Varying p

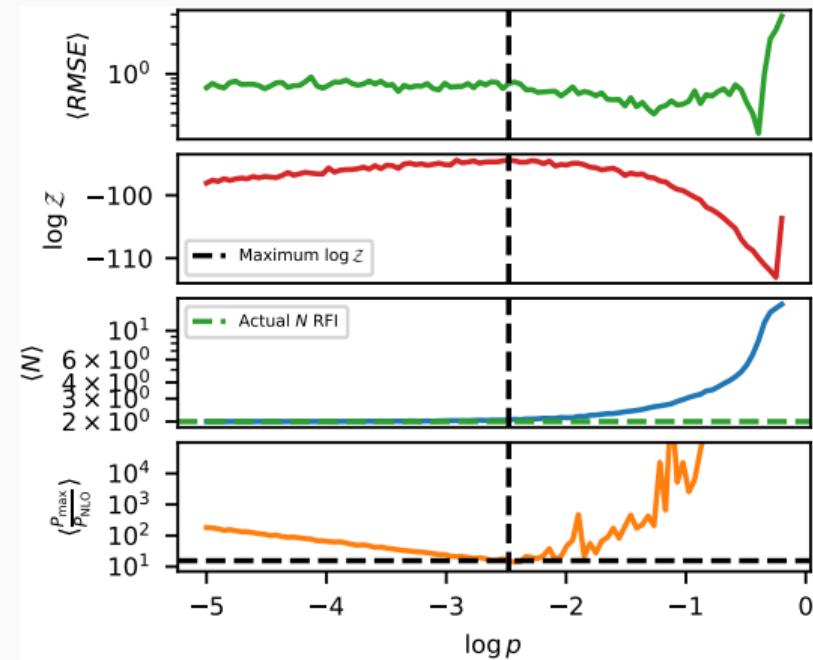


Varying p



Selection strategy for p .

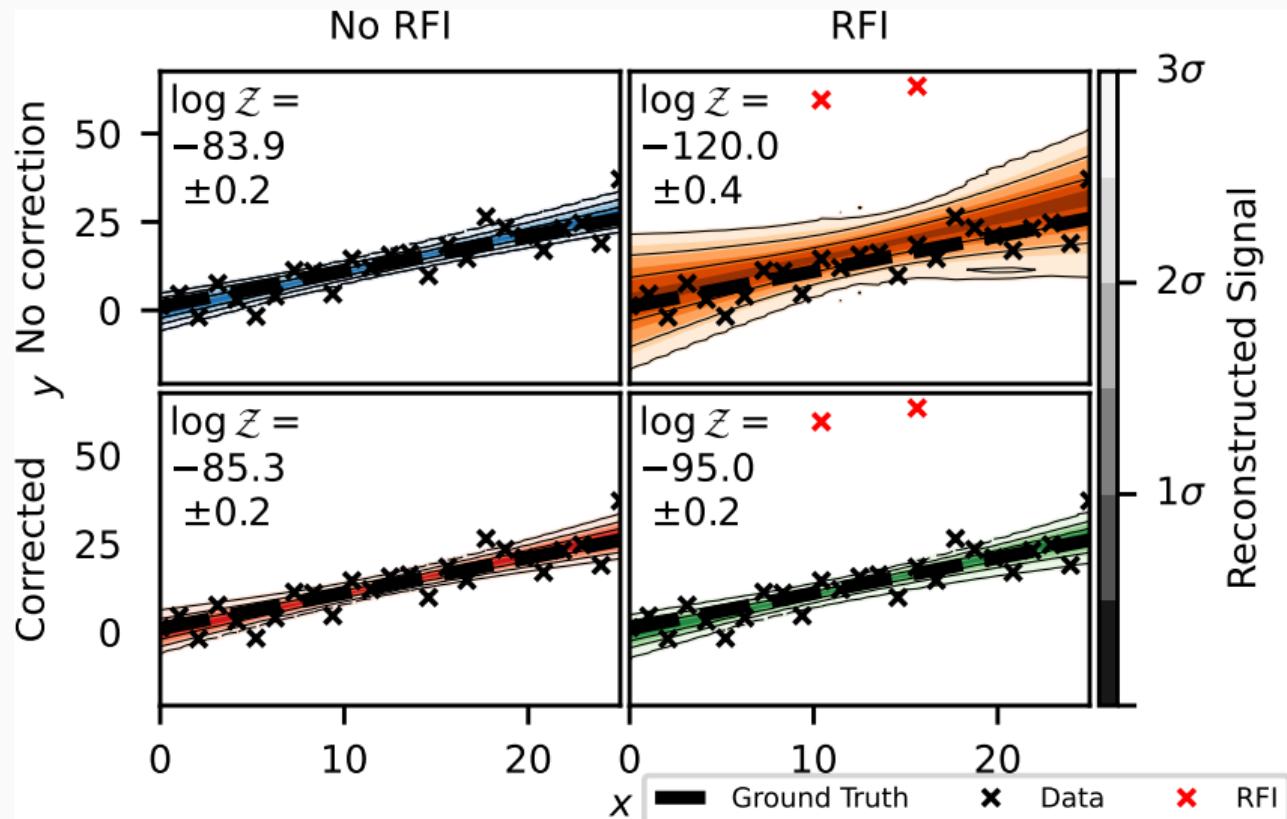
- ‘Select p such that the Bayesian evidence is maximised’



Fully automated anomaly detection

- Putting a prior on p , we can fit it dynamically as a free parameter.
- This fully automates the anomaly detection process.
- Must exclude $p = 0$.

Application to toy model



Implement with 2 lines of code

```
41
42 def likelihood(theta):
43     sig = theta[0]
44     logL = -(f_noise - window)**2/sig**2/2 - np.log(2*np.pi*sig**2)/2
45     return logL, []
46
34
47 def likelihood(theta):
48     sig = theta[0]
49     logL = -(f_noise - window)**2/sig**2/2 - np.log(2*np.pi*sig**2)/2 + np.log(1-p)
50     emax = logL > logP - np.log(delta)
51     logPmax = np.where(emax, logL, logP - np.log(delta)).sum()
52
53     return logPmax, []
54
```

Tutorial @ github.com/samleeney

Bayesian approach to radio frequency interference mitigation

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Interfering signals such as radio frequency interference from ubiquitous satellite constellations are becoming an endemic problem in fields involving physical observations of the electromagnetic spectrum. To address this we propose a novel data cleaning methodology. Contamination is simultaneously flagged and managed at the likelihood level. It is modeled in a Bayesian fashion through a piecewise likelihood that is constrained by a Bernoulli prior distribution. The techniques described in this paper can be implemented with just a few lines of code.

DOI: [10.1103/PhysRevD.108.062006](https://doi.org/10.1103/PhysRevD.108.062006)

arxiv: 2211.15448

Apply on Ia supernovae

Standard vs. Anomaly Detection Likelihoods

Standard Likelihood:

$$\log \mathcal{L}_{\text{std}} = -\frac{1}{2} \sum_i \left(\frac{f_i - m_i}{\sigma_i} \right)^2 - \frac{1}{2} \sum_i \log(2\pi\sigma_i^2) \quad (10)$$

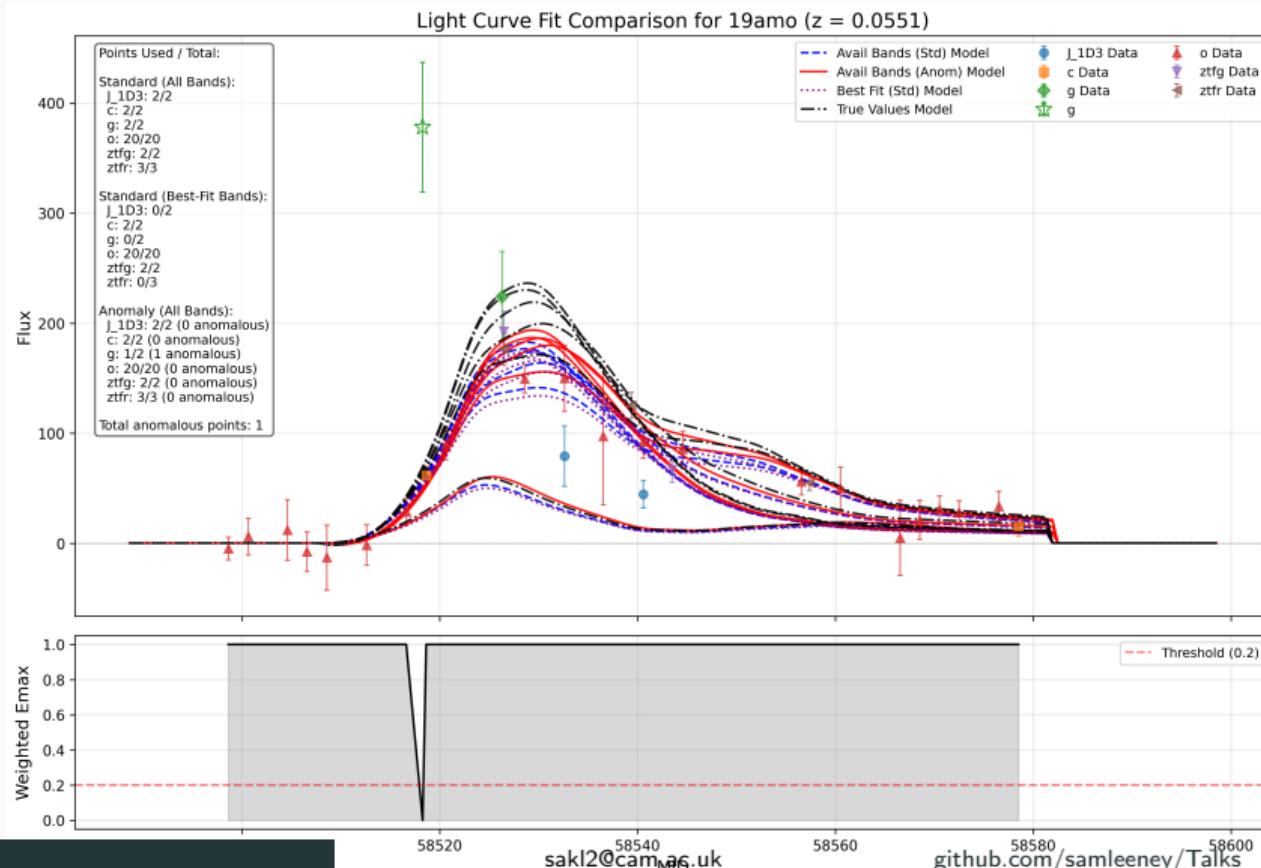
- f_i : Observed flux
- m_i : Model flux (SALT3)
- σ_i : Flux uncertainty

Anomaly Detection Likelihood:

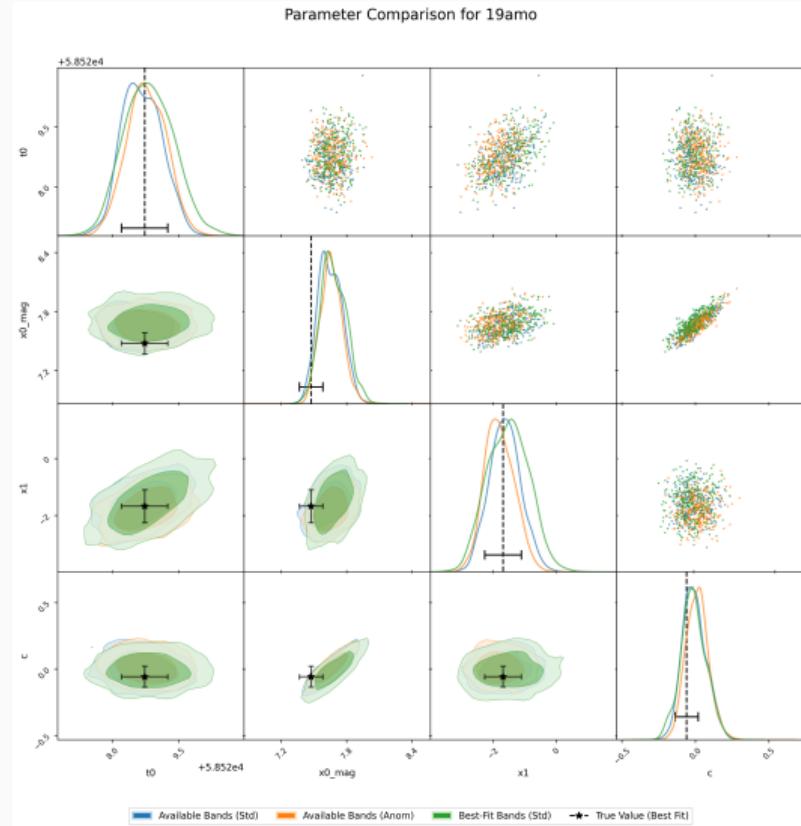
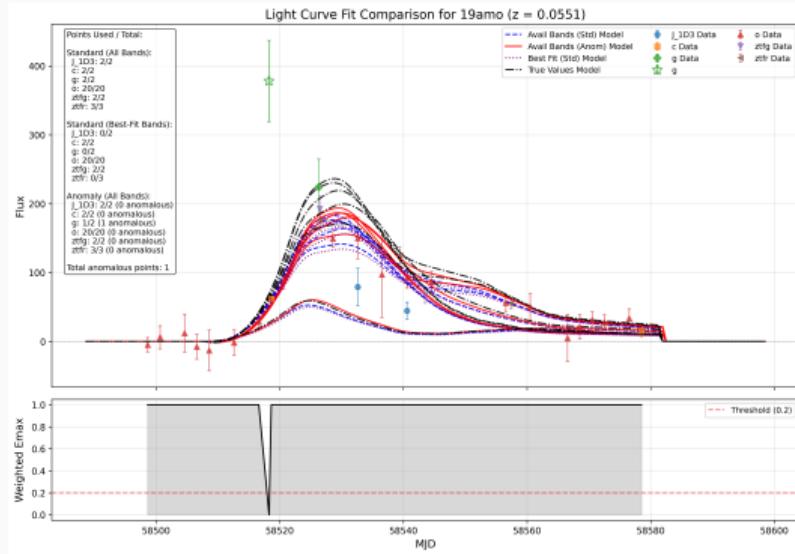
$$\log \mathcal{L}_{\text{anom}} = \sum_i \begin{cases} \log \mathcal{L}_i + \log(1 - p), & \text{if } e_i^{\max} \\ \log p - \log \Delta, & \text{otherwise} \end{cases} \quad (11)$$

- $\log \mathcal{L}_i$: Point-wise standard likelihood
- p : Anomaly probability (fitted parameter)
- e_i^{\max} : Boolean indicating normal data
- Δ : Maximum flux range

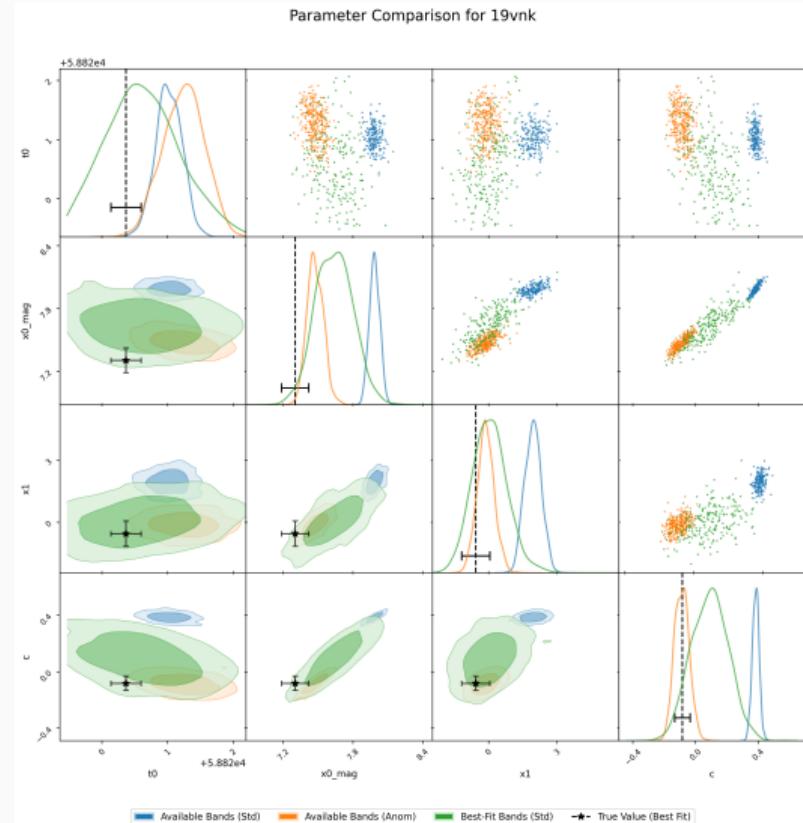
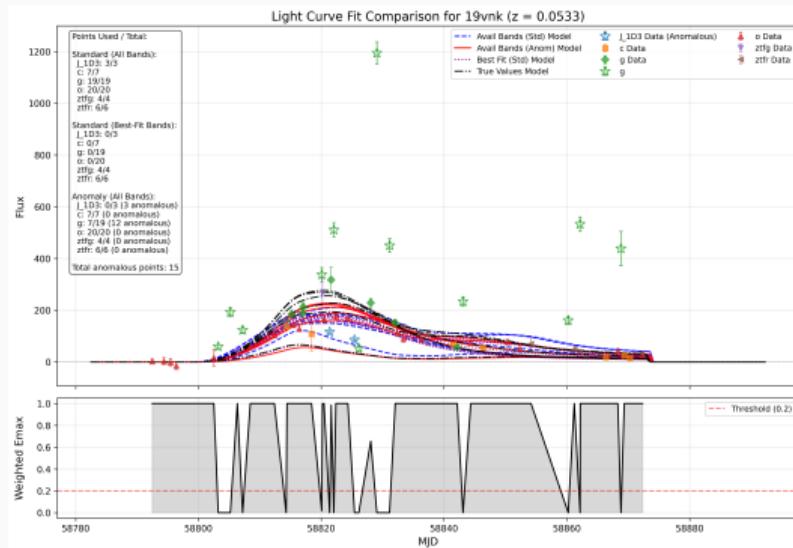
Applying to Ia supernovae



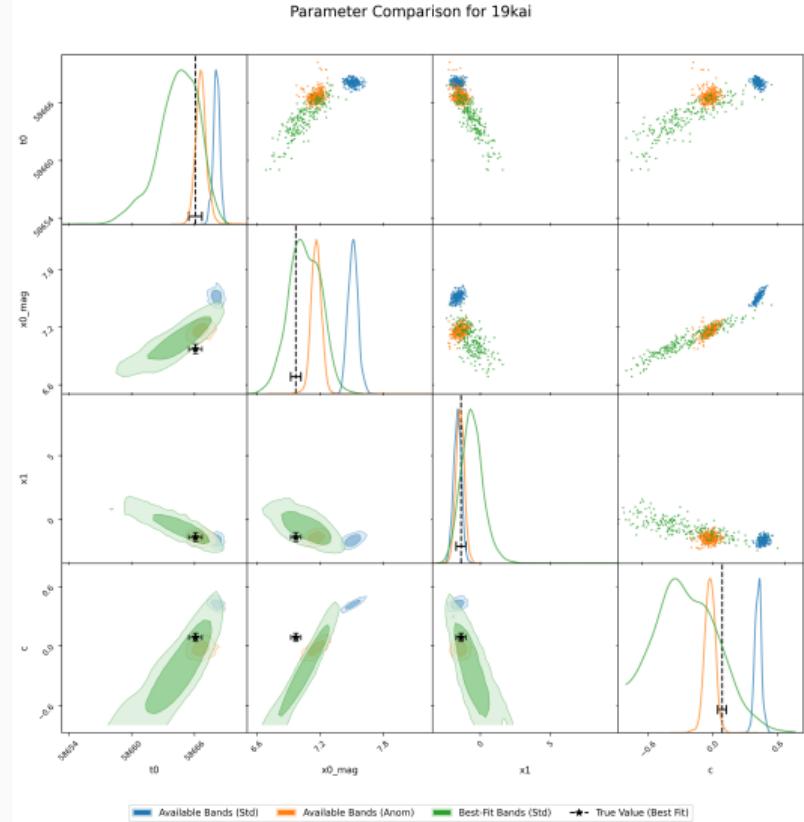
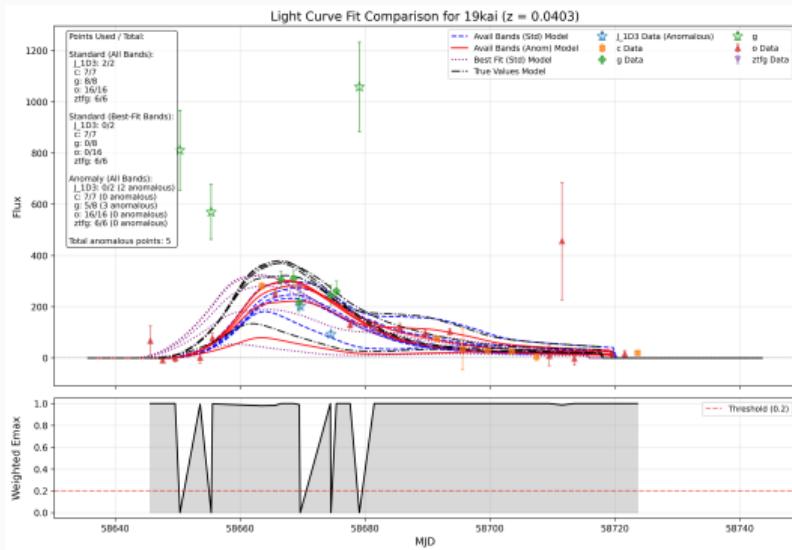
SN 19amo: Classic 'anomaly detection' example



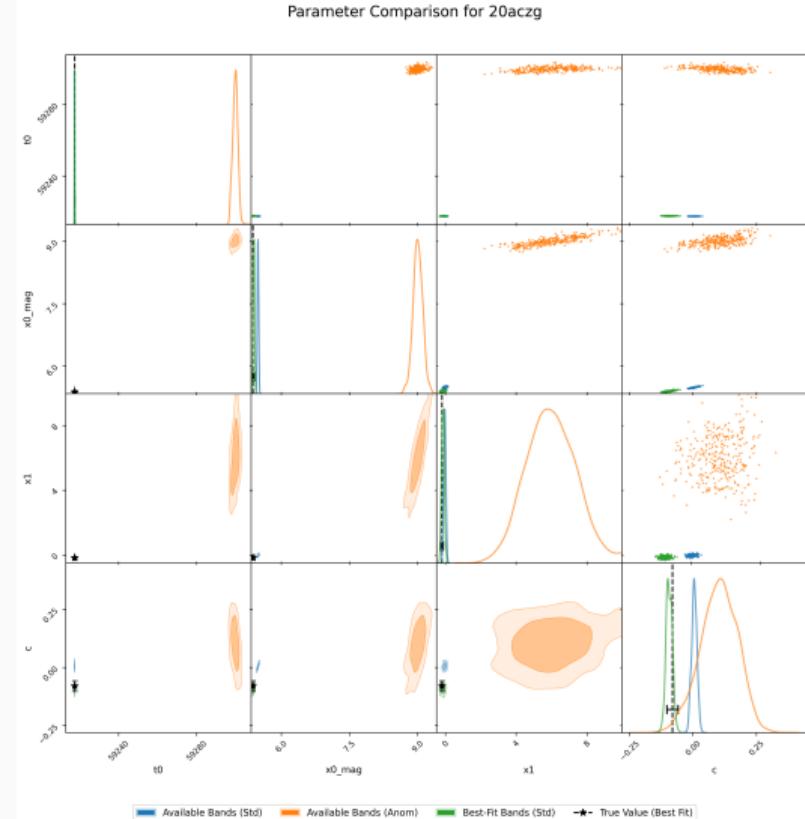
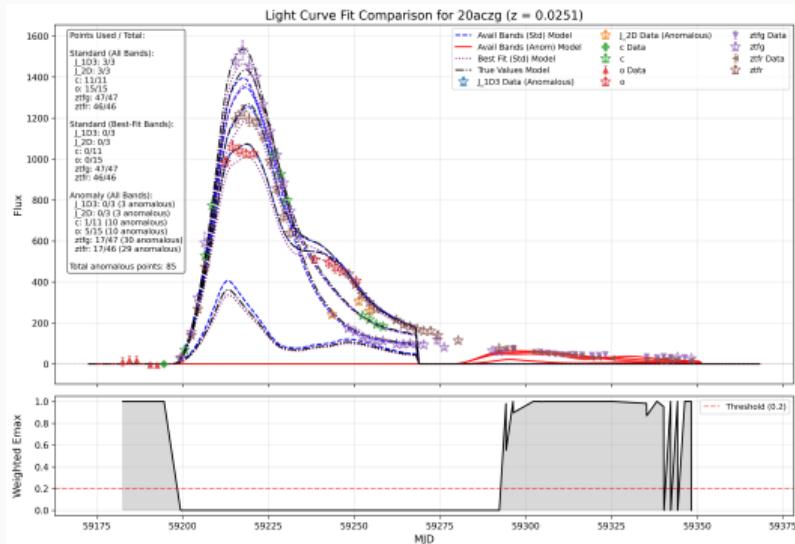
SN 19vnk: Automatic filter removal



SN 19kai: Flagging while preserving some data



SN 20aczg: Light Curve and Corner Plot Comparison



Key points

1. Standard flagging.

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2. Automated filter selection.

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1. Standard flagging.
2. Automated filter selection.
3. Data preservation from previously discarded filters.
4. Potentially can flag non Ia automatically?

Next steps

- Assess Hubble diagrams
 - Quantify impact on cosmological parameter estimation
 - Compare with traditional outlier rejection methods
 - Evaluate systematic error reduction
- Try on other datasets?
 - Apply to different supernova surveys (ZTF, LSST)
 - Test with different photometric systems
 - Evaluate performance across redshift ranges